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Sequence Learning in an Online Serial Reaction Time Task: The Effect of Task Instructions

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The serial reaction time task (SRTT) is commonly used to study motor learning and memory. The task is traditionally administered in a lab setting with participants responding via button box or keyboard to targets on a screen. By comparing response times of sequential versus random trials and accuracy across sequential trials, different forms of learning can be studied. The present study utilized an online version of the SRTT to study the effects of instructions on learning. Participants were randomly assigned to an explicit learning condition (with instructions to learn the visual sequence and associated tone) or an implicit learning condition (without instructions). Stimuli in both learning conditions were presented in two phases: auditory and visual (training phase), followed by auditory only (testing phase). Results indicated that learning occurred in both training and testing phases, as shown by a significant decrease in response times. There was no significant main effect of learning condition (explicit or implicit) on sequence learning. This suggests that providing explicit instructions does not seem to influence sequence learning in the SRTT learning paradigm. Future online studies utilizing the SRTT should explore varying task instructions in a parametric manner to better understand cognitive processes that underlie sequence learning.

***Keywords**:* explicit learning, implicit learning, online study, training and testing in sequence learning

Sequence learning is an important aspect of human behavior enabling the organization of skills, words, memories, and events. A prominent paradigm for studying sequence learning is the serial reaction time task (SRTT), which has been utilized to study differences between introspective and performance measures of learning (Nissen & Bullemer, 1987). Since then, the SRTT has been widely employed to study human behavior ranging from cognitive to biological precepts of memory and learning (Destrebecqz et al., 2005; Keele et al., 2003; Lissek et al., 2013; Schendan et al., 2003). The SRTT is used to study procedural learning, where participants are asked to identify a visual stimulus—usually in the form of

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four spatially placed squares appearing horizontally on the screen—by pressing the key corresponding to the position of the observed visual stimulus (Cohen et al., 1990; Nissen & Bullemer, 1987; Stark-Inbar et al., 2017; Zhuang et al., 1998). In a typical experiment, once a target selection has been made, the trial ends and is followed by a fixed delay known as the response stimulus interval, lasting between 200 and 500 ms (Robertson, 2007). With each subsequent trial, participants show perceptual motor sequence learning by performing faster in the sequential trials thereby showing a decrease in response time (RT), as compared with the randomized trials (Cohen et al., 1990; Deroost & Soetens, 2006; Martini et al., 2013; Willingham & Goedert-Eschmann, 1999). Learning differences are then deduced by comparing RTs in sequential versus random trial blocks.

Willingham et al. (2002) proposed using the SRTT to compare conscious and unconscious skill learning by manipulating it to be an implicit or explicit task. The SRTT can be utilized as an implicit task where the participants are never instructed about the sequence, and the sequence is learned procedurally (Nissen & Bullemer, 1987; Reber & Squire, 1994; Reed & Johnson, 1994). The SRTT can also be utilized as an explicit task, where participants are informed about the sequence and are tasked with learning it. This kind of explicit knowledge has previously been shown to result in faster performance, since participants are able to consciously anticipate the location of a successive target (Curran & Keele, 1993). Using functional neuroimaging to capture the effects of awareness on brain activation and behavior, Willingham et al. (2002) manipulated the participant's awareness of the sequence by instructing them that a specific color of visual stimulus corresponds to the sequence, while keeping them unaware of another color of visual stimuli playing another sequence. Participants were aware of learning one sequence but remained unaware of learning another sequence. By manipulating between these conditions of explicit and implicit sequence learning, the results showed that when there is a trade-off between awareness and performance, modulation takes place within the same neural network for procedural learning, regardless of whether learning is or is not followed by explicit knowledge of the task (Willingham et al., 2002).

Similar to using visual stimuli for sequence learning, researchers have also utilized auditory stimuli to study the effects of repeating tone sequences on sequence learning (Gottselig et al., 2004). Incorporating repetitive auditory stimuli has been shown to help with learning, while deviating from identical repetition pattern results in a catastrophic impact on sequence learning (Gottselig et al., 2004; Monaghan & Rowson, 2008). It has also been shown that relevant versus irrelevant tones affect sequence learning, for instance, when visual stimuli corresponds to a specific or relevant tone RT's are faster, whereas when visual stimuli correspond to random or irrelevant tones RTs as slower (Robinson & Parker, 2016). Hence, incorporating auditory stimuli, along with visual stimuli in the SRT task paradigm can support sequence learning, as it has the potential to help participants recall the sequence faster.

Given the contribution of auditory and visual stimuli influencing sequence learning behavior as previously described, further research has helped explicate two theories that have centered around the SRT task: One theory revolves around the separation of implicit and explicit neural processes and states that there are independent or competitive interactions in the neural system for implicit and explicit knowledge acquisition (Albert et al., 2020; Ashby et al., 1998; Reber & Squire, 1994; Smith et al., 2006; Stark & Squire, 2000; Willingham et al., 2002).

Another theory focuses on the memory system as being a single or a tightly integrated system (Cleeremans & Jiménez, 2002; Shanks & Perruchet, 2002; Wilkinson & Shanks, 2004).These theories go about understanding the acquisition of sequence learning in two different ways: The independent memory system theory proposes a slight role of explicit knowledge in sequence learning, meaning that explicit learning provides initial support in order to establish a routine, after which, the implicit learning processes take over for perfecting the skill being learned. Whereas, the single-system model maintains that explicit learning is the driving mechanism behind sequence learning through which a skill becomes refined overtime. The single-system approach can also be contrasted with the theory of automaticity in sequence learning, which proposes that by increasing the strength of a particular memory, automaticity can be established with little to no attention required for a given task (Logan, 1979; Posner & Snyder, 2004). Research surrounding these theories has helped elucidate the paths that center around understanding the acquisition of sequence learning, but an approach to better understand implicit and explicit learning is to determine how explicit knowledge—in the form of instructions—of the task contributes to learning itself.

Several studies have shown that data obtained from online experiments can be replicated from in-person experiments (Huber & Gajos, 2020; Sævland & Norman, 2016). Yet, there are still a limited number of experiments conducted online pertaining to learning and memory. Here we set out to develop and use an online SRT task paradigm, which utilizes visual and auditory stimuli to better understand the role of task instructions by randomizing participants into one of two conditions: the explicit (with instructions to learn the visual sequence and associated tone) or implicit (without these instructions) learning condition (Figure 1a). The current study used auditory (pure tones) stimuli in addition to the visual stimuli, a typical stimulus of the SRTT. These tones correspond with the four locations of the spatially placed squares on the screen. In the present study, we used sounds that have a sinusoidal waveform and have been previously used with the SRTT (Zhuang et al., 1998). The study consisted of two phases: auditory and visual (training phase) and auditory only (testing phase), and participants completed both phases. In the training phase, the visual stimulus appears, participants choose the keypress associated with the position where the visual stimulus was seen, and the keypress causes an auditory tone to sound, which is unique to that keypress. On the other hand, in the testing phase of the study, only the auditory stimulus is played, and the participant is tasked with recreating the sequence learned in the training phase of the study. No associated visual stimulus was presented in the testing phase, only auditory stimuli corresponding to the letters was presented.

Participants were randomly assigned into the explicit learning (with instructions) or the implicit learning (without instructions) conditions, to understand the effect of instructions on sequence learning in an online environment. We hypothesized that participants in the explicit learning condition will be faster and more accurate in the testing phase of the study, compared with participants in the testing phase in the implicit learning condition, as those in the explicit condition are provided instructions to learn the sequence previously in the training phase.

In addition, we hypothesized that RTs and accuracy will decrease and increase, respectively, during both the training and testing phases, as participants carry out each subsequent trial block. To examine motor sequence learning in the

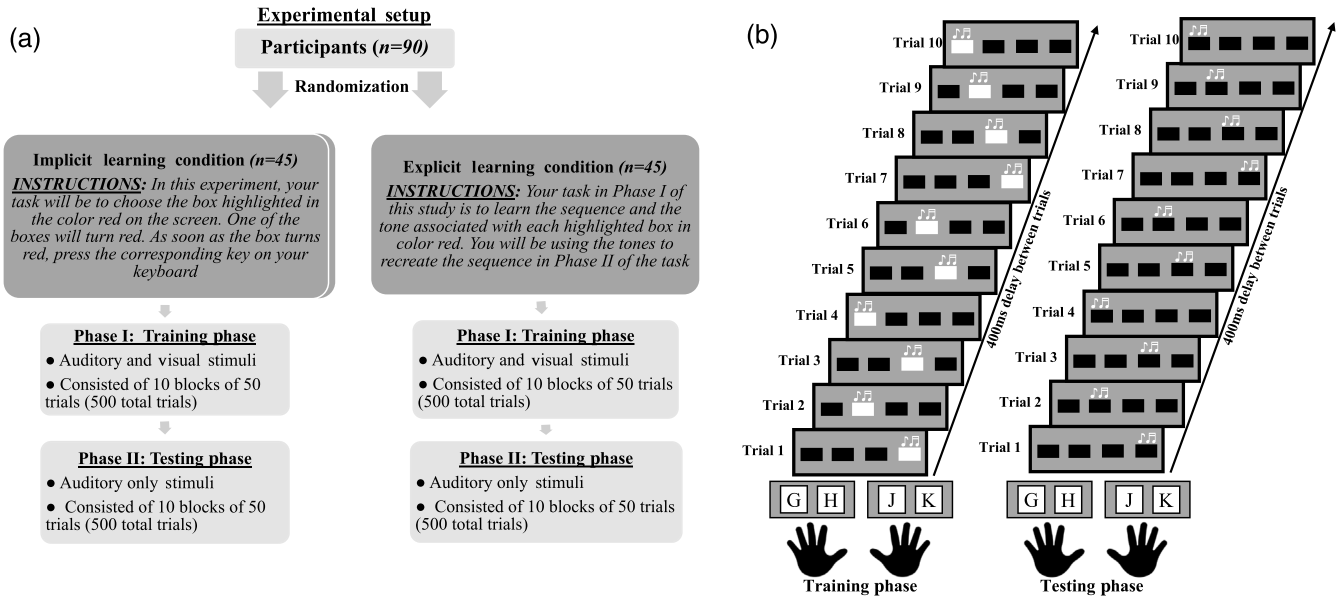

Figure 1 — (a) Between-subject experimental design for the online experiment. Participants were randomized into either the implicit or the explicit learning condition and were provided specific instructions based on the learning condition. Once randomized, participants completed both the training and testing phases in the study, which consisted of 10 blocks of 50 trials each for a total of 500 trials. (b) Schematic of the training and the testing phase in both explicit and implicit learning conditions.

SRTT, we compared RTs and accuracy of responses between the two learning conditions. The goals of the present study are twofold: testing the effect of task instructions in an SRTT paradigm by randomly assigning participants to the explicit or implicit learning conditions, while making use of both the auditory and visual stimuli; and to determine whether the SRTT paradigm can be employed online to study sequence learning.

Method

Participants

One hundred and six undergraduate students were recruited via the SONA research participant system. Participants were randomized into either explicit learning (with instructions to learn the visual sequence and associated tone) or implicit learning (without instructions to learn the visual sequence or associated tone) conditions. Sixteen participants were excluded from the data analysis due to incomplete and/or inconsistent data. Those with incomplete data did not finish the study, whereas those with inconsistent data had multiple blocks of trials with a RT of 5,000 ms, which indicated the end of trial as a response was not selected from the participant. This resulted in a total of 90 participants, with 45 in the explicit condition and 45 in the implicit condition. Of the 90 participants included in the study, 75 were female, 13 were male, one was third gender/nonbinary, and one preferred not to answer. The average age across all participants was 20.9 ± 2.4 years, and the age range was 18–37 years. In addition, an online embedded version of the Edinburgh Handedness Questionnaire was completed by each participant in the study and yielded the following handedness across the 90 participants: right handed—62 participants, ambidextrous—24 participants, and left handed—four participants (Oldfield, 1971; Zhang, 2014). The experimental protocol was approved by the institutional review board at the University of California (Merced). All participants provided informed consent.

Stimuli

Both conditions included two phases: auditory and visual (training phase) and auditory only (testing phase). In the training phase of the study, we used 350-ms pure sine tones at the following frequencies: 500, 1,000, 1,500, 2,000 Hz. These pure tones were associated with the following letters on the keyboard: G, H, J, and K, respectively. The keyboard sequence for the sequential trials was K–H–J–G–J–H–K–J–H–G in Blocks 2, 3, 4, 5, 7, 8, and 9, and the keyboard sequence for the catch trials was G–H–K–H–G–K–G–J–G–J in Blocks 1, 6, and 10, during both phases. There were two learning conditions in the study: explicit and implicit. In the explicit learning condition, participants were provided the following instructions to learn the sequence and tone: *Your task in Phase I of this study is to learn the sequence and the tone associated with each highlighted box in color red. You will be using this sequence in Phase II of the task.* Whereas in the implicit learning condition, the participants were not alerted to the sequence and provided with the following instructions: *In this experiment, your task will be to choose the box highlighted in the color red on the screen. One of the boxes will turn red. As soon as the box turns red, press the corresponding key on your keyboard.*

The training phase followed this pattern: while the visual cue to the sequential and/or the catch trials is shown on the participant's screen, participants choose the correct keypress, which was followed by the sine pure tone sound. Participants were given 5,000 ms to respond to the visual cue, after which the trial automatically ends, and the new visual cue is presented. Each trial was separated by a 400-ms intertrial interval. Each block—consisting of 50 trials—was separated by a 15-s break.

In the subsequent testing phase of the study, participants were provided with only the auditory cue. This means that one of the four pure tones would play (500 Hz—G, 1,000 Hz—H, 1,500 Hz—J, and 2,000 Hz—K), and the participants have 5,000 ms to choose the key they think is associated with that tone, after which the trial automatically ends, and the new auditory cue is presented. Each trial is separated by a 400-ms intertrial interval, and each block—consisting of 50 trials—is separated by a 15-s break. After the end of the testing phase, participants were asked posttask questions pertaining to the sequence they learned in the task. Participants were asked if, and when they noticed a sequence, when they learned the sequence, and if they could reproduce the sequence to the best of their ability.

Experimental Paradigm

An online version of the SRTT was created using labs.js and deployed via Qualtrics (Henninger et al., 2019). Informed consent forms were signed, and the Edinburgh Handedness questionnaire was completed via Qualtrics online survey, and a keyboard device was necessary for participation. Participants were then randomly assigned to either the explicit or the implicit learning condition. Prior to starting the study, a sound calibration step was completed, where the participants were required to use earphones or headphones to adjust the sound level, they were comfortable with and respond to the softest/quietest sound presented. The sound calibration ensured that the auditory stimuli was presented properly and was audible to the participants, while the required use of earphones/headphones ensured that participants were able to fully engage with the task. If the sound calibration step was not completed successfully, the study automatically discontinued the participant.

After the sound calibration step, participants were provided with a short familiarization session pertaining to the letters they would be using in the trial (G, H, J, and K) using the left middle finger and left index finger for letters G and H, respectively; and using the right index finger and right middle finger, for letters J and K, respectively. Familiarization was only performed prior to the initial training phase of the study and consisted of a practice block with five trials to acclimatize participants to the location of their fingers on the keyboard, how the keypresses were performed, along with the pure tones that were utilized in the study. Once the familiarization portion was completed, participants began the training phase of the study, followed by the testing phase. The sequences used in the present study were adapted from Nissen and Bullemer (1987).

In the training phase of the study, four black squares appeared at the center of the participant's screen. Each of the black squares were associated with a letter of the keyboard (G, H, J, and K). The setup of the training phase can be seen in Figure 1b. The participant's task was to choose the appropriate square when it turned red and respond by keypress on the associated letter as quickly and as accurately as possible. Once the correct response was made by the participant, it was followed by a pure tone associated with each letter as follows: G (500 Hz), H (1,000 Hz), J (1,500 Hz), and K (2,000 Hz). In the testing phase of the study, four black squares appeared at the center of the participant's screen. The setup of the testing phase can be seen in Figure 1b. The participant's task was to listen to the auditory stimuli and based on the frequency of the tone, choose the letter best associated with that tone. Both training and testing phases consisted of 10 blocks of 50 trials, where Blocks 1, 6 and 10 were catch trials blocks.

Posttask Questionnaire

All participants completed posttask questionnaires in both the explicit and the implicit learning conditions. The posttask questionnaires for the explicit learning condition probed the participant's knowledge for the sequence and the tones associated with each letter in the sequence learned during the task. While all the participants were aware of the sequence and the associated tones, seven out of the 45 participants in the explicit learning condition guessed the correct sequence length and were able to provide partial composition of the sequence. The posttask questionnaire for the implicit learning condition also probed for sequence and tone association knowledge. None of the 45 individuals correctly guessed the length or composition of the sequence.

Data Analysis

Median RTs for correct trials were calculated for each block for each participant and a group mean was then calculated by averaging individual means in each block. The median RT was used here so as to estimate the central tendency of the RT distribution, while at the same time negating the influence of skewness and outliers (Wilcox & Rousselet, 2018). The blocks were mean centered in order to rescale predictors for each block in both conditions. Finally, the RT data were log transformed to normalize the data, reduce the effects of outliers, and maintain good power (Whelan, 2008). To account for accuracy across trials, the percentage error in each participant's response was computed for each block of trials and was then calculated by averaging individual's means across each block.

Statistical Analyses

All analyses were conducted in R (version 1.3.1093). Linear mixed-effects (LMEs) regression models were fitted using the lme4 package (Bates et al., 2015). To analyze RT data and accuracy data, we utilized LME models which explicitly account for variation in our data contributed to by each block and participant in the RT model and by each participant in the accuracy model (Gałecki & Burzykowski, 2013; Winter, 2019).

Results

Median RT

Median RTs for each block of the training and the testing phases are plotted in Figure 2a and 2b, respectively. Participants in the explicit learning condition had lower RTs on repeated sequential trials than on catch trials, with the training phase having a mean of 346.9 ms (*SD* = ±83.3) versus 414.2 ms (*SD* = ±177.8) and the testing phase with a mean of 732.1 ms (*SD* = ±256.4) versus 845.7 ms (*SD* = ±177.8), respectively. Similarly, participants in the implicit learning condition also had lower RTs on the repeated sequential trials than on catch trials, with the training phase having a mean of 338 ms (*SD* = ±85) versus 386.3 ms (*SD* = ±72.8) and the testing phase with a mean of 705.3 ms (*SD* = ±273) versus 794.4 ms (*SD* = ±243), respectively.

To examine the sequence-specific learning in both the explicit and implicit learning conditions, a series of LMEs were fit to the RTs of each trial block, using trial type (sequential and catch) and block and their interaction as predictors. To account for between-subject variances in RTs, random intercepts for participants and blocks were added. In the explicit learning condition, results from training phase revealed significant main effects of sequential trials, $\beta = -0.04$; $SE = 0.02$; $p = .012$, and blocks trials, $\beta = -0.04$; $SE = 0.01$; $p < .001$, affirming that participants responded faster during the sequential trials and their overall reaction time decreased as they progressed through each subsequent block. On the other hand, in the implicit learning condition, results from the training phase revealed significant main effects of blocks only trials, $\beta = -0.03$; $SE = 0.01$; $p < .001$, indicating that while RT decreased in subsequent blocks, the trial type did not reach significance suggesting that participants did not learn the sequence structure (Table 1).

Results from the explicit learning condition's testing phase revealed a significant main effect of blocks trials, $\beta = -0.05$; $SE = -0.05$; $p < .001$, indicating a decrease in RT over subsequent block; but the nonsignificance of trial type seems to suggest that learning of the sequence structure was not maintained during the testing phase. Finally, results from the implicit condition's testing phase revealed a significant main effect of blocks trials, $\beta = -0.05$; $SE = 0.01$; $p < .001$, indicating a decrease in RT over subsequent block, and a nonsignificant effect of trial type suggesting that participant were not able to implement the sequence structure (Table 2).

Accuracy

Accuracy of participant responses in the sequential trials in the training phase was higher than in the testing phase for both the explicit and implicit learning conditions. The average accuracy in the explicit condition for the training phase was 97.5% (*SD* = ±3%), compared with the testing phase, which was 58.9% (*SD* = ±25.8%). The average accuracy in the implicit condition for the training phase was 97.1% (*SD* = ±3%), compared with the testing phase, which was 57.6% (*SD* = ±25.1%).

To examine accuracy across different the training and testing phases in both learning conditions, a series of LME models were fit to the accuracy of each trial block using trial type (sequential and catch) as a predictor. To account for between-subject variances in RTs, random intercepts for participants were added. In the explicit learning condition, results from the training phase showcase significant main effect of sequential trials, $\beta = 0.01$; $SE = 0.003$; $p = .024$, indicating that participants in the sequential trials were more accurate. The implicit learning condition's training phase also indicated a significant main effect of sequential trials, $\beta = 0.01$; $SE = 0.003$; $p = .009$, indicating higher accuracy in sequential blocks (Table 3).

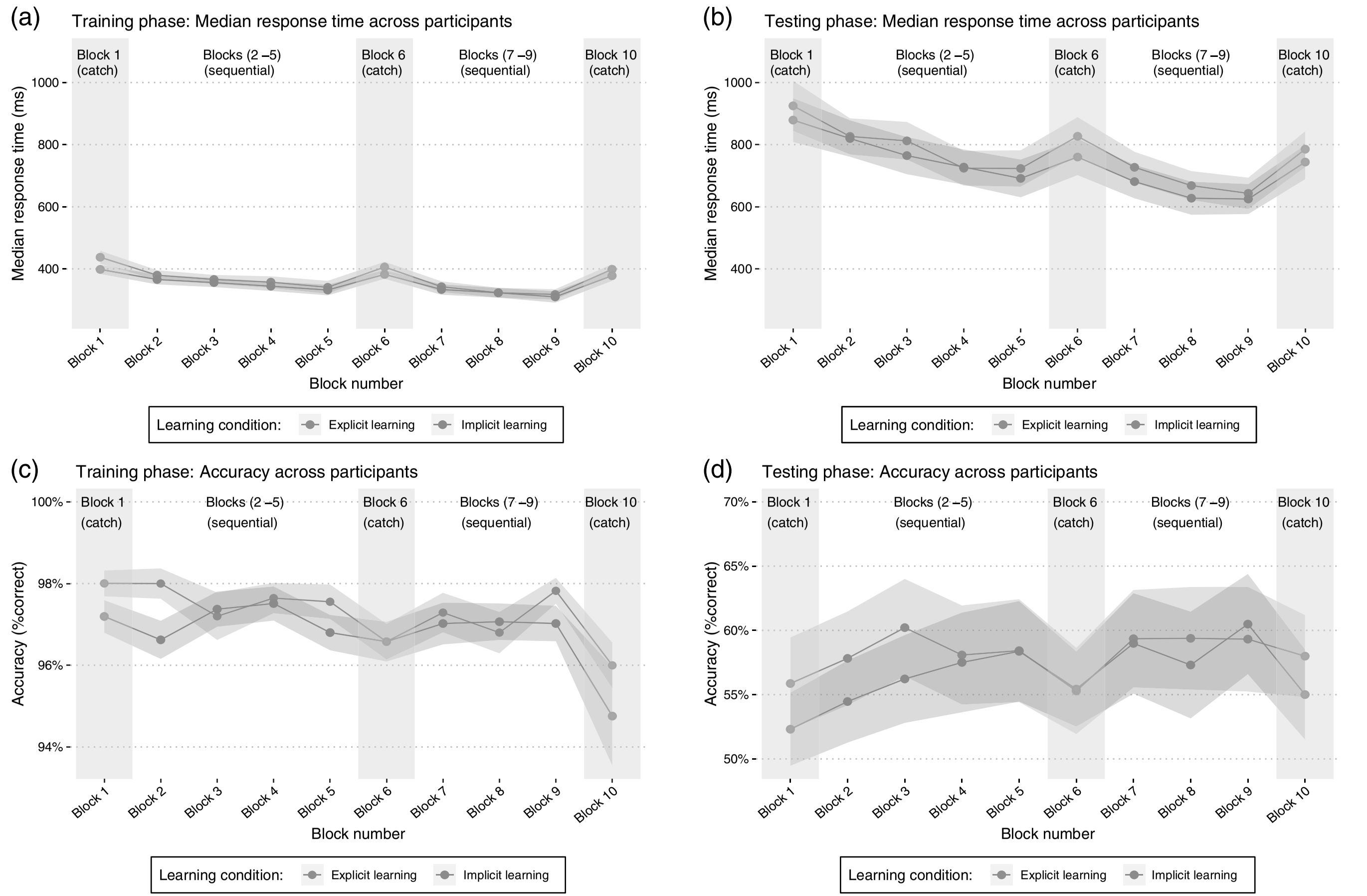

Figure 2 — (a) Mean of the median response time across 45 participants in the training phase of the explicit and the implicit learning conditions. The shaded region indicates standard error. Catch trials in blocks 1, 6, and 10 are shown. (b) Mean of the median response time across 45 participants in the testing phase of the explicit and implicit learning conditions. The shaded region indicates standard error. (c) Accuracy plot of the training phase. The shaded region indicates standard error. (d) Accuracy plot of testing phase. The shaded region indicates standard error. Note: Accuracy plots in (c) and (d) have different scales on the *y*-axis to emphasize the overall accuracy pattern, 94–100% and 50–70%, respectively.

Table 1 Results From the Linear Mixed-Effect Regression of RT in the Training Phase for Explicit and Implicit Learning Conditions, Respectively

	Explicit learning condition			Implicit learning condition		
	Training phase			Training phase		
	β	*SE*	*p* (χ^2)	β	*SE*	*p* (χ^2)
Fixed effects						
Intercept	5.89	0.04	**<.001**	5.85	0.04	**<.001**
Trial type (sequential)	–0.04	0.02	**.012**	–0.03	0.02	.080
Blocks	–0.04	0.01	**<.001**	–0.03	0.01	**<.001**
	Groups		***SD***	**Groups**		***SD***
Random effects	Participant	Intercept	0.22	Participant	Intercept	0.23
		Blocks	0.06		Blocks	0.04
	Residual		0.11	Residual		0.01
	Observations: 450			Observations: 450		
Full model	(log [response time]) ~ trial type × blocks + (1 + blocks ∣ participant)					

Note. There is a significant main effect of blocks and sequential trials in the training phase of the explicit learning condition and a significant main effect of blocks only in the implicit learning condition. Bolded values indicate statistical significance of $p < .05$.

Accuracy results from the explicit and implicit testing phase reveal a significant main effect of sequential trials, $\beta = 0.03$; $SE = 0.01$; $p = .009$, and, $\beta = 0.03$; $SE = 0.01$; $p = .001$, respectively. This suggests that accuracy in the sequential trial was remained high during the testing phase (Table 4).

Discussion

The goal of the present study was to test whether there was an effect of task instructions in sequence learning in the implicit and explicit learning conditions by utilizing both auditory and visual stimuli in the SRTT paradigm. This was measured by randomly assigning participants to one of the two learning conditions: implicit or the explicit learning condition and comparing RT and accuracy measures. In addition, RT and accuracy were compared for each of the two phases—training and testing phase—of the study. The graphical overview of RT in Figure 2a and 2b and accuracy in Figure 2c and 2d, along with statistical analysis confirm that we see the expected interaction effects in the training phase of the study for both conditions: Participants in both the implicit and the explicit learning conditions respond significantly faster and more accurately to the stimuli in each subsequent trial block, consistent with prior SRTT studies (Robertson, 2007). On the other hand, in the testing phase of the study, while participants are significantly fast in each trial subsequent block, they are more inaccurate (for comparison: 99% accuracy in

Table 2 Results From the Linear Mixed-Effect Regression of RT in the Testing Phase for Explicit and Implicit Learning Conditions, Respectively

	Explicit learning condition			Implicit learning condition		
	Testing phase			Testing phase		
	β	*SE*	*p* (χ^2)	β	*SE*	*p* (χ^2)
Fixed effects						
Intercept	6.58	0.05	**<.001**	6.47	0.06	**<.001**
Trial type (sequential)	–0.01	–0.03	.700	0.06	0.03	.064
Blocks	–0.05	–0.05	**<.001**	–0.05	0.01	**<.001**
	Groups		***SD***	**Groups**		***SD***
Random effects	Participant	Intercept	0.33	Participant	Intercept	0.35
		Blocks	0.06		Blocks	0.05
	Residual		0.19	Residual		0.05
	Observations: 450			Observations: 450		
Full model	(log [response time]) ~ trial type × blocks + (1 + blocks ∣ participant)					

Note. There is a significant main effect of blocks only in both the explicit and implicit learning conditions.

Table 3 Results From the Linear Mixed-Effect Regression of Accuracy Data in the Training Phase for Explicit and Implicit Learning Conditions, Respectively

	Explicit learning condition			Implicit learning condition		
	Training phase			Training phase		
	β	*SE*	*p* (χ^2)	β	*SE*	*p* (χ^2)
Fixed effects						
Intercept	0.97	0.003	**<.001**	0.96	0.004	**<.001**
Trial type (sequential)	0.01	0.003	**.024**	0.01	0.003	**.009**
	Groups		***SD***	**Groups**		***SD***
Random effects	Participant	Intercept	0.01	Participant	Intercept	0.02
	Residual		0.03	Residual		0.03
	Observations: 450			Observations: 450		
Full model	Accuracy ~ trial type + (1 + participant)					

Note. There is a significant main effect of sequential trials in both the learning conditions.

Table 4 Results From the Linear Mixed-Effect Regression of Accuracy Data in the Testing Phase for Explicit and Implicit Learning Conditions, Respectively

	Explicit learning condition			Implicit learning condition		
	Testing phase			Testing phase		
	β	*SE*	*p* (χ^2)	β	*SE*	*p* (χ^2)
Fixed effects						
Intercept	0.56	0.04	**<.001**	0.54	0.03	**<.001**
Trial type (sequential)	0.03	0.01	**.009**	0.03	0.01	**.001**
	Groups		***SD***	**Groups**		***SD***
Random effects	Participant	Intercept	0.23	Participant	Intercept	0.22
	Residual		0.10	Residual		0.10
	Observations: 450			Observations: 450		
Full model	Accuracy ~ trial type + (1 + participant)					

Note. There is a significant main effect of sequential trials in both learning conditions.

training phase for both implicit and explicit condition vs. 59.9% and 63.9% accuracy in testing phase for implicit and explicit condition, respectively). This inaccuracy in the testing phase is consistent across both learning conditions indicating that instructions did not play a significant part in sequence learning in this study. In addition, compared with training phase, the testing phase had higher RTs for both the explicit and the implicit learning conditions, 732.1 ms ($SD = \pm 256.4$) and 705.3 ms ($SD = \pm 273$), respectively. This is due to the use of the auditory only stimuli here, indicating that despite being aware of the tone association with each letter from the training phase, participants were slow to respond in the testing phase. Furthermore, previous research suggests when conducting same-day learning tasks auditory recognition tends to be coarser, compared with visual recognition, indicating that the increase in RT when participants are presented with the auditory only stimuli could be related to the slow auditory recognition during the testing phase of the task (Gloede & Gregg, 2019; Lindner et al., 2009). Also, it is important to note the fact that these RT values are higher than typically seen in laboratory experiments. It is also possible that the higher than usual values could be due to the online nature of the experiments presented here.

The use of the training and testing phases makes this study different from prior studies. The training phase utilizes both visual and auditory modalities to acquaint the participants with the task, whereas the testing phase asks the participants to use their learning to recreate the sequence that was learned in the training phase. Prior research has shown that the visual system dominates the auditory system when stimuli were presented simultaneously (Colavita & Weisberg, 1979; Egeth & Sager, 1977). But recently it has been shown that the auditory system dominates when temporal information is being processed, suggesting that the auditory system can provide a quantitative advantage over the visual system (Conway & Christiansen, 2005). A recent study investigating the effects of audition on sequence learning via the SRTT showed that utilizing tones that correlate with the location of the visual stimulus increased participant RTs (Robinson & Parker, 2016). Based on these findings, instructing the participants in one condition (i.e., explicit learning) to learn pure tones, primes those participants to focus on learning the auditory sequence, whereas participants in the other condition (i.e., implicit learning) are not primed in a similar manner.

The absence of advantage in the explicit learning condition is consistent with the independent memory systems theory, which suggests only a slight role of explicit knowledge in sequence learning, whereby after providing initial support, a routine is established, and the implicit learning process takes over. While the results from the current study did not support the effect of instructions on the two learning conditions, it is possible to adjust the study by adding components such as providing a lengthier familiarization session to parse the effects of instructions in a sequence learning task. It has been shown that initial performance is based on having explicit memory that can be formed through explicit instructions and having longer familiarization sessions can aid in understanding this phenomena and further optimize sequence learning (Abrahamse et al., 2013). Another possibility is dividing the sequence length into chunks—whereby participants are able to recognize or group information into smaller fragments that are easily stored in the working memory—which makes learning and retaining sequential information easier (Gilchrist, 2015). These methods have the potential to capture the effects of instructions in an SRTT paradigm by providing task appropriate training and reliable methods to retain the learned sequence.

To summarize, the online study reported here revealed that instructions did not influence performance in sequence learning during the testing phase of the explicit learning condition when compared with the implicit learning condition. The results reported here regarding using the SRTT are comparable to the traditional lab version of the SRTT despite having been implemented in an online setting. Learning effects were as expected and can be seen in decreasing RTs with each subsequent trial in both learning conditions. But the instructional effect could not be replicated, and this could be due to possible differences in the online platforms being used. It was recently shown that using a range of devices, operating systems, and experimental platforms for an online study can lead to inconstantly in accuracy, precision of display, and response timing, contributing to variability in online data collection (Anwyl-Irvine et al., 2021). One possible way to use an online platform is by restricting participant setups for one specific browser to minimize differences between each participant's setup that can lead to variable data. In addition to consolidating platforms, differences in RTs have been shown when participants perform sequence learning tasks during different times of the day (Doyon et al., 2009; Roth et al., 2005; Vakil et al., 2022). In addition to consolidating platforms, differences in RTs have been shown when participants perform sequence learning tasks during different times of the day (Doyon et al., 2009; Roth et al., 2005; Vakil et al., 2022). Hence, restricting the time of the day when participants complete the study has the potential improve sequence learning overall. The lack of control over the specific time of implementation of the experiment due to its online nature was one of the limitations of the present study.

While one of the many advantages of conducting an online study is the ability to collect data from a large sample size in a relatively short amount of time, one of the disadvantages is the impracticality of having long experiments, that is, longer than 60 min (Sauter et al., 2020). As such, it would be more appropriate to conduct a two-session study by including a familiarization session, where the effects of sequence learning via instructions can be observed. Recent studies have demonstrated the viability and usefulness of using online platforms for data collection. (Kulikowski & Potasz-Kulikowska, 2016) have shown that the effects n-back performance task can be seen in overall accuracy and reaction time measures when administered online. Similarly, Tsay et al. (2021) had participants perform visuomotor rotation tasks online and showed that the results obtained were comparable to those obtained from previous lab studies. This line of research sets a promising example and comparable manipulations—that are more accessible to a wider population than those in a standard lab—that can potentially be implemented for the SRT task to further study the effects of motor sequence learning outside a controlled lab environment, especially during a pandemic when it is otherwise difficult to test human subjects in a traditional lab setting.

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